Power System Dynamic Estimation

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General Description

Abstract

Developing methods for state estimation and system identification are essential for increasing the reliability of the power grid. Typically this problem has been solved on steady state time scales, however faster dynamics are becoming more important and with the deployment of phasor measurement units (PMUs) fast estimation is now possible. To do this fast estimation a layered architecture that integrates state estimation, change point detection, and disturbance classification is used. By thinking of these estimation algorithms along with controls as a layered system it improves our ability to design optimal architectures that are both fast and flexible. State Estimation can be achieved using Kalman filtering and particle based techniques which assume a system topology and dynamics model. These techniques are adapted to the differential algebraic equations that describe the power system and their robustness is explored. Using these estimates we can make predictions of the future outputs which then are compared to the PMU data to identify unexpected deviations. These change points then trigger a topology change classifier to identify the new topology of the system after a fault and also triggers a fault tracker to track the state through faults that are cleared. Finally, questions of general architecture design are raised such as how to optimally link these estimation modules and optimally place sensors to achieve all these objectives.

Introduction

Objective:

Develop an architecture to track the dynamic state and topology of a power system over fast, sub-second, time scales that can then be used to make control decisions.

Power System Model:

Differential Algebraic Equations

ODEs:
- Machine Models
- Exciter Models
- Turbine Governor Models

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{y}, \mathbf{u})$$

Equality Constraints:
- Bus Power Injections
- Machine Constraints
- Control Constraints

$$\mathbf{0} = \mathbf{g}(\mathbf{x}, \mathbf{y}, \mathbf{u})$$

Output:
- PMUs

$$\mathbf{z} = \mathbf{h}(\mathbf{x}, \mathbf{y}, \mathbf{u})$$

Variables

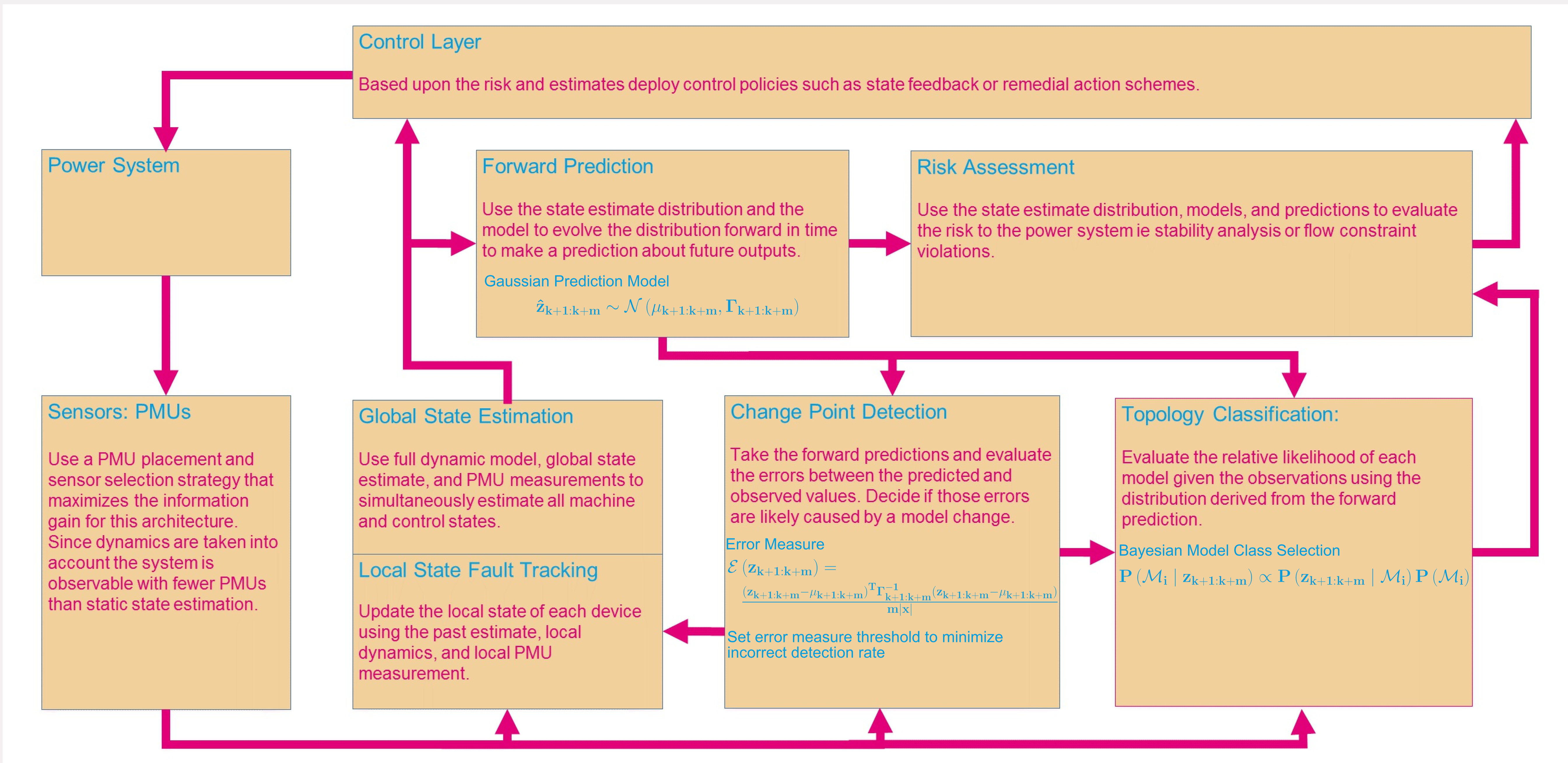
x : Dynamic State
- Generator Angles, Frequencies, Axis Voltages
- Control Internal States

y : Algebraic Variables
- Bus Voltages
- Generator Field Voltages, Powers, Torques
- Control Constraints

u : Inputs

z : Observations
- Bus Voltages

Power System Estimation and Control Architecture



Global and Local State Estimation Details

State Estimation

Extended Kalman Filter

Nonlinear System

$$\mathbf{x}_k = \mathfrak{F}(\mathbf{x}_{k-1}) + \mathbf{w}_k$$
$$\mathbf{z}_k = \mathfrak{H}(\mathbf{x}_k) + \nu_k$$

Prediction

$$\left.\begin{aligned} \hat{\mathbf{x}}_{k|k-1} &= \mathfrak{F}(\hat{\mathbf{x}}_{k-1|k-1}) \\ \mathbf{P}_{k|k-1} &= \mathbf{F}_{k-1}\mathbf{P}_{k-1|k-1}\mathbf{F}^T_{k-1} + \mathbf{Q}_k \\ \mathbf{F}_{k-1} &= \frac{\partial \mathfrak{F}}{\partial \mathbf{x}}\Big|_{\hat{\mathbf{x}}_{k-1|k-1}} \end{aligned}\right\} \text{State } \mathbf{x} \sim \mathcal{N}(\hat{\mathbf{x}}, \mathbf{P})$$

$$\left.\begin{aligned} \hat{\mathbf{z}}_{k|k-1} &= \mathfrak{H}(\hat{\mathbf{x}}_{k|k-1}) \\ \mathbf{S}_{k|k-1} &= \mathbf{H}_k\mathbf{P}_{k|k-1}\mathbf{H}^T_k + \mathbf{R}_k \\ \mathbf{H}_k &= \frac{\partial \mathfrak{H}}{\partial \mathbf{x}}\Big|_{\hat{\mathbf{x}}_{k|k-1}} \end{aligned}\right\} \text{Output } \mathbf{z} \sim \mathcal{N}(\hat{\mathbf{z}}, \mathbf{S})$$

Correction

$$\mathbf{K}_{k|k-1} = \mathbf{P}_{k|k-1}\mathbf{H}^T_k\mathbf{S}^{-1}_{k|k-1}$$
$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_{k|k-1}(\mathbf{z}_k - \hat{\mathbf{z}}_{k|k-1})$$
$$\mathbf{P}_{k|k} = (\mathbf{I} - \mathbf{K}_{k|k-1}\mathbf{H}_k)\mathbf{P}_{k|k-1}$$

Numerical Integration Methods

Euler:

$$\mathbf{x}_k = \mathbf{x}_{k-1} + \mathbf{f}(\mathbf{x}_{k-1}, \mathbf{y}_{k-1})\Delta t$$
$$\mathbf{0} = \mathbf{g}(\mathbf{x}_{k-1}, \mathbf{y}_{k-1})$$
$$\mathbf{0} = \mathbf{g}(\mathbf{x}_k, \mathbf{y}_k)$$

Predictor Corrector:

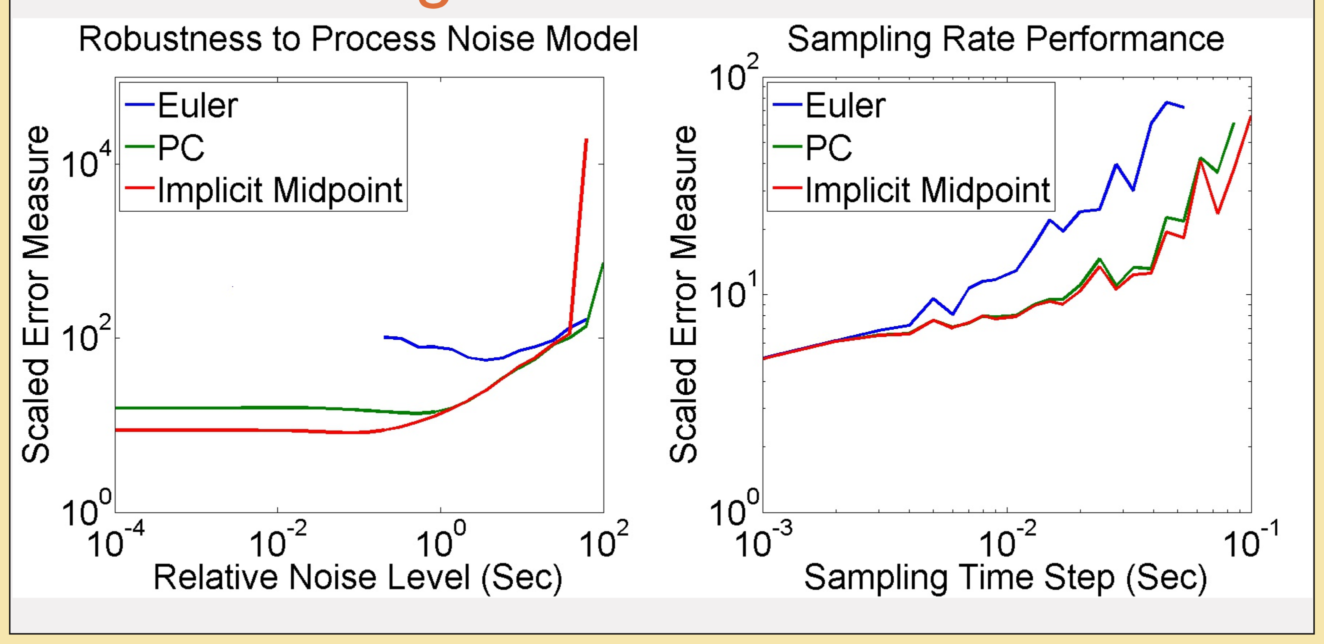
$$\mathbf{x}_k = \mathbf{x}_{k-1} + \frac{\Delta t}{2}(\mathbf{f}(\mathbf{x}_{k-1}, \mathbf{y}_{k-1}) + \mathbf{f}(\tilde{\mathbf{x}}_k, \tilde{\mathbf{y}}_k))$$
$$\tilde{\mathbf{x}}_k = \mathbf{x}_{k-1} + \Delta t \mathbf{f}(\mathbf{x}_{k-1}, \mathbf{y}_{k-1})$$
$$\mathbf{0} = \mathbf{g}(\mathbf{x}_{k-1}, \mathbf{y}_{k-1})$$
$$\mathbf{0} = \mathbf{g}(\tilde{\mathbf{x}}_k, \tilde{\mathbf{y}}_k)$$
$$\mathbf{0} = \mathbf{g}(\mathbf{x}_k, \mathbf{y}_k)$$

Implicit Midpoint:

$$\mathbf{x}_k = \mathbf{x}_{k-1} + \frac{\Delta t}{2}(\mathbf{f}(\mathbf{x}_{k-1}, \mathbf{y}_{k-1}) + \mathbf{f}(\mathbf{x}_k, \mathbf{y}_k))$$
$$\mathbf{0} = \mathbf{g}(\mathbf{x}_{k-1}, \mathbf{y}_{k-1})$$
$$\mathbf{0} = \mathbf{g}(\mathbf{x}_k, \mathbf{y}_k)$$

Solve discrete DAE with Newton's Method

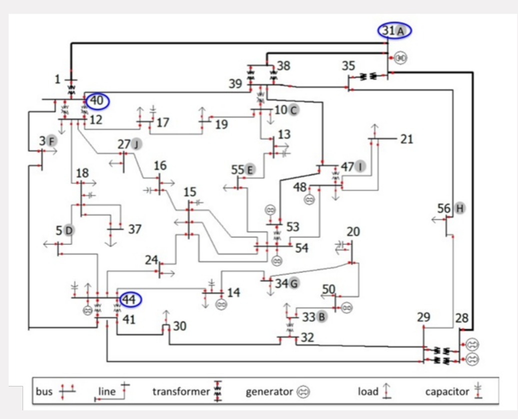
Integration Robustness

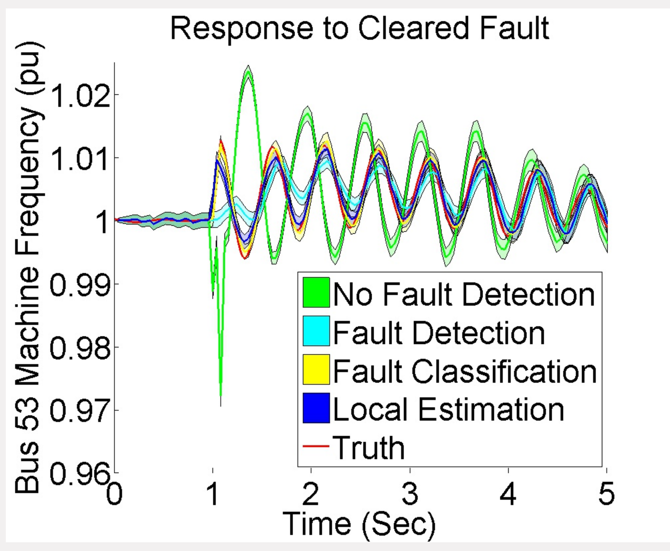


Test System

Thirty Seven Bus System

PSAT implementation of a PowerWorld test system with thirty seven buses, nine machines and seven turbine governors. A three phase fault occurs at bus 54 and is cleared.





Fault Handling

Local State Evolution

Local Variables

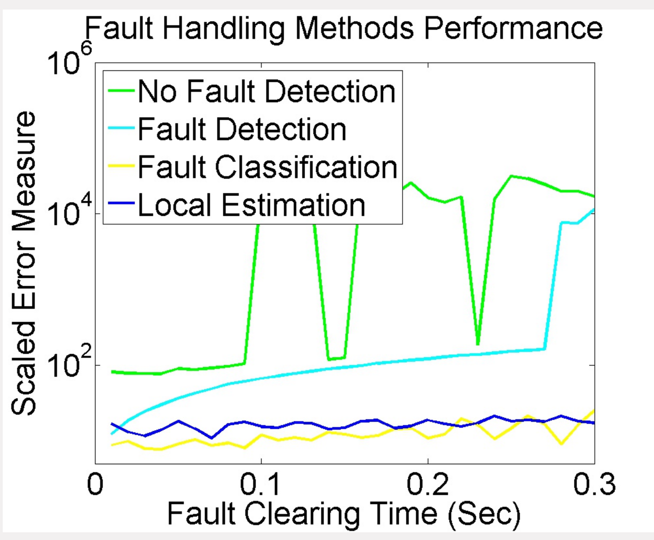
$$\mathbf{x} = [\delta, \omega, \mathbf{e}'_q, \mathbf{e}'_d, \vec{x_c}]^T \Big\} \text{Local Machine and Control States}$$
$$\mathbf{u} = [\mathbf{v}, \theta]^T \Big\} \text{Local Bus Voltage as Input}$$
$$\mathbf{y} = [\mathbf{i}_q, \mathbf{i}_d]^T \Big\} \text{Local current as Algebraic Variable}$$

Solve Local Dynamics

$$\mathbf{x}_k = \mathbf{x}_{k-1} + \frac{\Delta t}{2}(\mathbf{f}(\mathbf{x}_{k-1}, \mathbf{y}_{k-1}, \mathbf{u}_{k-1}) + \mathbf{f}(\mathbf{x}_k, \mathbf{y}_k, \mathbf{u}_k))$$
$$\mathbf{0} = \mathbf{g}(\mathbf{x}_{k-1}, \mathbf{y}_{k-1}, \mathbf{u}_{k-1})$$
$$\mathbf{0} = \mathbf{g}(\mathbf{x}_k, \mathbf{y}_k, \mathbf{u}_k)$$

Global Uncertainty Propagation

$$\mathbf{F}_k = \left[\frac{\partial \mathbf{x}_k}{\partial \mathbf{x}_{k-1}} \frac{\partial \mathbf{x}_k}{\partial \mathbf{v}_{k-1}} \frac{\partial \mathbf{x}_k}{\partial \mathbf{v}_k}\right]$$
$$\Sigma_{k-1|k-1} = \mathbf{cov}(\mathbf{x}_{k-1}, \mathbf{u}_{k-1}, \mathbf{u}_k)$$
$$\mathbf{P}_{k|k} = \mathbf{F}_k\Sigma_{k-1|k-1}\mathbf{F}^T_k + \mathbf{Q}$$



Conclusion

Discussion

Comments
- Robustness and performance can be improved by replacing the commonly used Euler's method with more advanced integration schemes
- Using a local estimation method drastically increases the ability of the estimator to track the system through a fault having almost as good performance as perfect classification

Accomplishments
- Demonstrated dynamic state estimation is possible for power systems and can track the state through faults
- Proposed a framework using these state estimates for change point detection and classification

Future Work
- Better characterize process and measurement noise distributions
- Developed better methods for uncertainty propagation particularly for prediction and local estimation

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